# Quantifying the Effects of Propagation on Classification of Cetacean Vocalizations

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## LONG-TERM GOALS

To develop a robust automatic classifier with a high probability of detection and a low false alarm rate that can classify vocalizations from a variety of cetacean species in diverse ocean environments.

## OBJECTIVES

In previous work as part of ONR grant N000141210139 a unique automatic classifier developed by the PI that uses perceptual signal features –features similar to those employed by the human auditory system– was employed to successfully classify anthropogenic transients, and vocalizations from five cetacean species. Although this is a significant achievement, successful implementation of this (or any) classifier requires that it be temporally and spatially robust. The primary goal will be to address the question: "Will it work on vocalization data from these species collected under different environmental conditions?" To examine this, discriminant analysis will be used to rank the aural features in terms of their ability to separate the vocalizations between species. Then, the more highly ranked features will be tested for robustness. This will be done by performing a propagation experiment using cetacean vocalizations and synthetically generated calls as source signals, and testing the received signals with the classifier. The measurements will be complemented by comparing experimental results to propagation model results with the goal of generalizing the results to other ocean environments.

## APPROACH

The research is part of a PhD program undertaken by Ms. Carolyn Binder under the supervision of Dr. Paul C. Hines. The postgraduate program is being conducted collaboratively in the Oceanography and

Electrical Engineering departments at Dalhousie University where Dr. Hines holds adjunct professor and research posts, and at Defence R&D Canada–Atlantic where Ms. Binder is a researcher.

Passive acoustic monitoring (PAM) is widely in use to study marine mammals; since marine mammals can be found in all ocean basins, their habitats cover diverse underwater environments. It is well known that acoustic propagation can vary substantially between environments which can result in distortion of acoustic signals [1-3]. This in turn, can lead to environment-dependent time-frequency characteristics of a received vocalization. The resulting distortion of vocalizations may impact the accuracy of PAM systems. Thus, to develop a classification system capable of operating in many environments one must understand the role of propagation on the classifier.

A prototype aural classifier developed at Defence Research and Development Canada has successfully been used for inter-species discrimination of cetaceans [4]. The aural classifier is an effective PAM tool because it employs perceptual signal features, which model features used by the human auditory system [5]. The proposed research aims to examine the robustness of this classifier, and the perceptual features it uses, to environmental conditions. To accomplish this, propagation experiments were conducted by transmitting a set of real and synthetic vocalizations from bowhead and humpback whales, and measuring the received signals at a variety of ranges [6]. The transmitted and received signals will be tested using the aural classifier to identify any performance degradation due to propagation. The measurements will be complemented by propagation-model results using environmental inputs measured during the experiments. The model results will provide physical insight into what propagation effects have the greatest impact on the classifier's robustness, and aid in generalizing the experimental results to other ocean environments. It also enables one to put bounds on realistic within-environment variability. It is worthy of mention that there is no study published in the literature that systematically analyzes the impacts of propagation on an automated classifier, using both underwater propagation experiments and complementary modeling.

If propagation does impact some features, then the next step is to rank the features in order of their sensitivity to propagation-related effects. Features which are especially sensitive to the acoustic environment might simply be removed from the aural classifier. Alternatively, it may be found that many of the perceptual features are environment-sensitive and therefore it is unreasonable to exclude all of them. In this case, a strategy may instead be developed to generate training sets for the classifier that take propagation-related signal distortion into account; this could be done either by acoustically distorting the training data by propagating them through a modeled environment or by including vocalizations in the training set that came from a variety of propagation ranges as done in [7, 8].

## WORK COMPLETED

The focus of the effort during FY 2015 has been two-fold:

1. Continuing detailed analysis of the data collected during the propagation experiments to test the robustness of the aural classification feature set. Details of the experiment are reported in [6] and are not repeated here due to space limitations, but a schematic of the experimental geometry is shown in
2. Figure **1**.
3. Exploring the relative impacts of signal-to-noise ratio (SNR) and multipath propagation effects on the performance of the classifier using a pulse propagation model.

*Experimental Data Analysis*: The acoustic data that were collected during the experiments were processed. The processing stream is as follows: The signals are identified in the recordings made by each hydrophone using a frequency band-limited energy detector [9]. These detections are then compared to the known time that signals were transmitted to remove false detections. After each signal has been detected, a four second segment of the signal is extracted with the detection located approximately in the centre of the segment. Each extracted detection is saved to a WAV file, and high-pass filtered to remove the DC-offset applied by the recording equipment and any low-frequency noise. At this point, the received signals are able to be input to the aural classification algorithm.

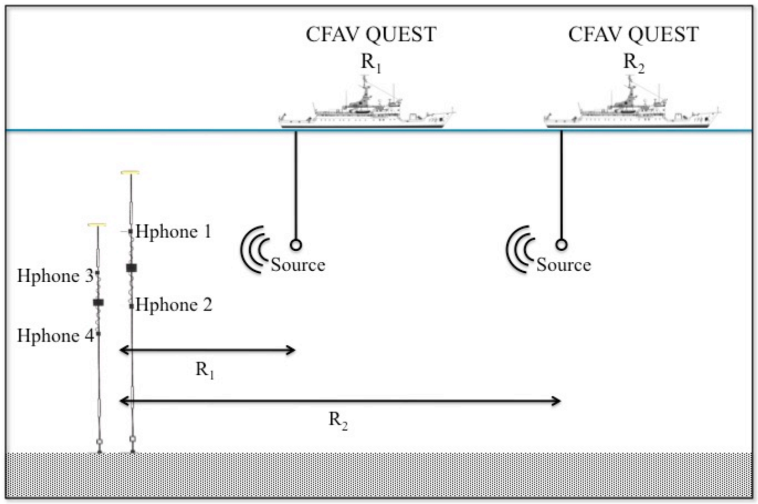


***Figure 1: : Representation of the experimental setup. The ship first deployed two hydrophone moorings, moved to the first location and transmitted the set of signals, then moved further away from the recorders and retransmitted the signals. R1 and R2 represent the horizontal range the signals propagated from the source to the midpoint between the moorings.***

The 58 perceptual features are calculated for each signal transmitted during the experiments and the signals received on each of the deployed hydrophones. An initial assessment of the classifier performance is accomplished by training the classifier on data recorded by a monitor hydrophone that was deployed from QUEST during the experiments, and testing on data transmitted through the water. Classification tasks are divided so that the real and synthetic whale calls will be considered separately.

The classifier is trained using all non-redudant features (see [5] for explaination of how highly-correlated, or redundant, features are identified) as determined from the signals in the training set. Examining and comparing the decision regions for signals transmitted over each of the ranges will allow qualitative analysis of the classifier's robustness. Quantitative analysis will consist of comparing the accuracies and area under the ROC curve AUCs, as well as the class means and variances. If propagation affects the perceptual features used for classification, then one would expect that the class means of the propagated signals in the training and testing sets would be significantly different, and/or there would be a large change in the variance of the classes. This will likely result in a decrease in the AUC and/or the classification accuracy. This type of analysis is repeated allowing the classifier-algorithm freedom to select the best perceptual features to train the classifier.

*Performance Dependence on SNR vs. Multipath Propagation:* Preliminary results from the experimental analysis (Figure 2) indicate that there is a trend of decreasing classifier performance with

increasing transmission range. A similar pattern was noted in the SNR-dependence investigation of Murphy and Hines [7], suggesting that SNR may, at least in part, be driving the decrease in classifier performance. Mouy et al. [10] also noted that false negative rates increased as SNR decreased. Thus, it is expected that there is a range-dependent component of the aural classifier performance that is due to decreasing SNR as the range increases. The question thus becomes, what are the relative contributions of lowering SNR and increasing multipath signal distortion to reduced classifier performance?

Pulse propagation modelling is used to address this question. DRDC's WATTCH (WAveform Transmission Through a CHannel) [11, 12] model is used to simulate the expected time series received at a set of hydrophones for each sourch signal based on the user-defined environment inputs. The propagatation modelling component is done using the active version of Bellhop. The WATTCH program was chosen because it allows for range-dependent environments, is efficient, and accuracte for the frequencies and spatial scales of the experiment. To examine the relative importance of SNR and propagation on classifier performance, a simulation study was developed that examined three separate cases:

*Case 1:* Add noise to the original signals (i.e., signals which were not transmitted during experiment or simulation). Snippets of noise recorded during the sea trial are added to the signals to match the SNR of signals that were recorded during the experiments for ranges equal to $R = \{0.07, 1, 5, 10, 20\}$ km.

*Case 2*: Use the WATTCH model to simulate signals propagated over range $R$.

*Case 3*: Add noise to simulated signals from case 2, to match the measured SNR at each value of $R$. This should provide the most realistic results, and match experimental results.

Classification performance for each of these cases is compared as a function of propagtion range.

**RESULTS**

Experimental classifier performance for the synthetic whale calls is summarized in Figure 2. The classifier was trained with data from a monitor hydrophone deployed from QUEST, separated from the acoustic source by approximately 70 m. The data transmitted over longer ranges is then run throught the trained classifier. Each line on the plot shows the performance determined from data recorded on a different hydrophone. Results are also separated by day. There is a clear trend for the classifier performance to decrease with increasing range. This is at least partially due to classifier performance decreasing with decreasing SNR, a trend that is obvious in the bottom panel of Figure 2. The question remains – what is the relative importance of SNR and multipath propagation effects to this range-dependent decrease in performance?

A modelling study was performed to examine this question by comparing classification performance as a function of range for the three cases discussed above. Results are shown in Figure **3**. As expected, the performance decreased as SNR decreased with increasing range, similar to what was observed in the experimental data. A suprising result here is that the performance remained perfect for the second case. Even though multipath propagation increasingly distorted the waveform with range, there was no change in the performance; however, when noise was added to these signals the performance decreased below that of the noise only case. This suggests that with sufficient SNR, multipath propagation has minimal impact on classifier performance; lowering the SNR however, not

only decreases performance, it amplifies the multipath-dependent degradation. Further work needs to be done to determine if there are (realistic) environments in which propagation effects drive performance and whether surface roughness needs to be included to to obtain sufficient fidelity in the model.

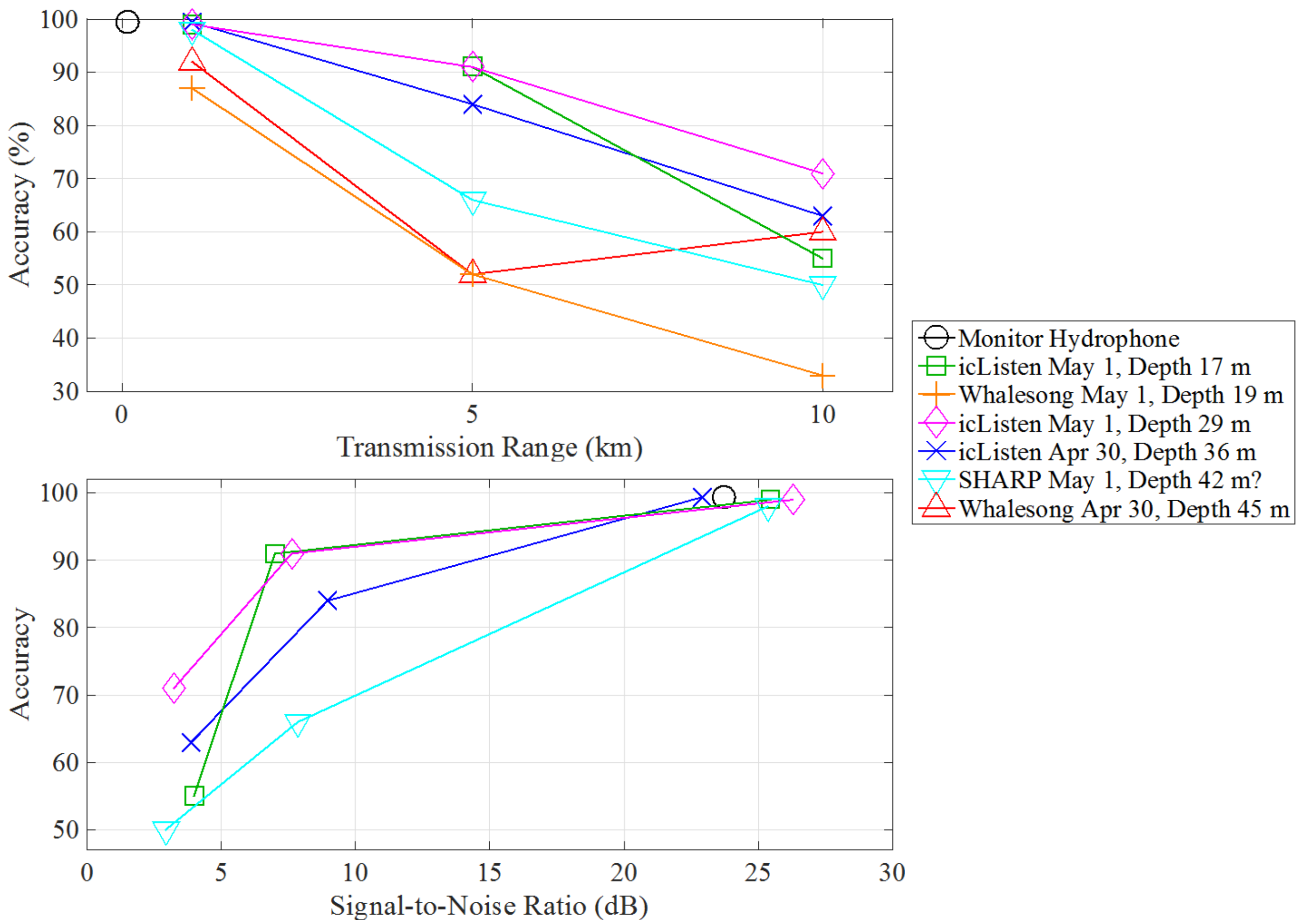


***Figure 2: Experimental classifier performance for bowhead and humpback synthetic calls as a function of transmission range (top) and SNR (bottom). The classifier was trained with data from a hydrophone deployed from QUEST and then validated on data from each of the recorders. The black circle in the plots represents the training results.***

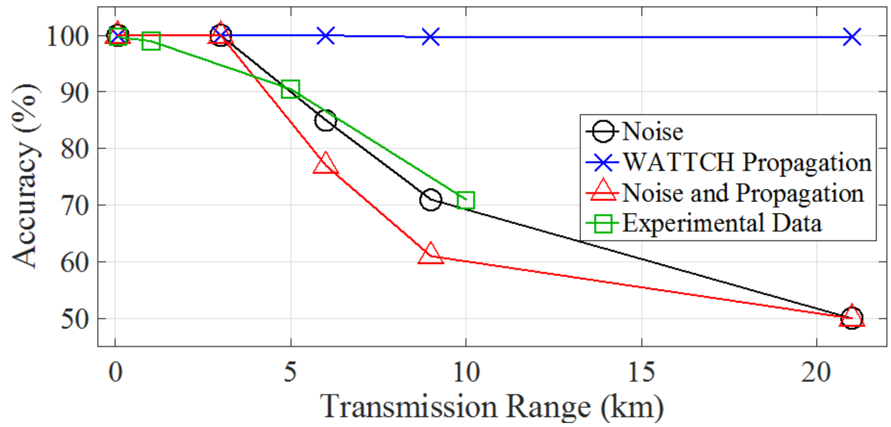


***Figure 3: Relative impacts on classifier performance of SNR and signal distortion due to multipath propagation as a function of transmission range. The classifier was trained with data from the 70 m range and applied to data transmitted over the longer ranges.***

## IMPACT/APPLICATIONS

Detection and classification of cetaceans has become critically important to the US Navy due to an ever increasing requirement for environmental stewardship. Passive acoustics continues to be the best method to carry out this task but current techniques provide only a partial solution; most detectors are either too general, leading to unacceptably high false alarm rates, or are too specialized (i.e., species- or location-specific) leading to many missed detections. Furthermore, future military platforms will have to support smaller complements and deal with ever-increasing data throughput, so that automation of on-board systems is essential. In addition, the technique is well suited to autonomous systems since a much smaller bandwidth is needed to transmit a classification result than to transmit raw acoustic data. The success of the machine classifier in discriminating cetacean vocalizations suggests that it could be applied to other passive acoustic classification problems which currently employ human audition. This would be particularly useful if expert listeners aren't available –such as diagnosing heart murmurs in remote communities that lack a cardiologist, or as part of the triage process in a hospital emergency department. Alternatively, the machine classifier is ideally suited when the sheer volume of data makes human audition untenable – such as classifying ocean acoustic data for species population monitoring. Finally, developing a robust classifier for passive marine mammal vocalizations is also a first step to testing the algorithm on passive transients generated by submarines to examine its potential for passive detection and classification of submarines.

## RELATED PROJECTS

This research will benefit from DRDC Atlantic's Force ASW Program in which DRDC's aural classification algorithms (including the marine mammal classification algorithm) is being integrated into DRDC's System Test Bed (STB). The STB is used to evaluate sonar algorithms in a military context. Two of the insights to be gained are: 1. Does the aural classifier reduce false alarms from marine mammals, thereby reducing operator workload and enabling greater concentration on potential threats? 2. Is the aural classifier easily integrated into a navy platform?

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## PUBLICATIONS


1. Paul C. Hines and Carolyn M Binder, "Quanitfying the effects of propagation on classification of cetacean vocalizations," DRDC Scientific Report DRDC-RDDC-2014-R103, 2014.


## HONORS/AWARDS/PRIZES

Carolyn Binder (Dalhousie Unversity/Defence R&D Canada – Atlantic):
1. Best PhD Talk, Conference for Dalhousie Oceanography Graduate Students, sponsored by Dalhousie University Oceanography Department.